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Automated Brain Tumor Classification Using Hybrid Deep Learning Models

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Abstract

The accurate and timely diagnosis of brain tumors remain a major challenge in medical imaging, traditionally dependent on radiologist expertise. To address this, we propose a hybrid deep learning framework that integrates computer vision models with transfer learning for improved brain tumor detection and classification. Our system combines the feature extraction capabilities of VGG16 and ResNet-50 into a hybrid VGG16–ResNet-50 model and leverages a fine-tuned EfficientNetB2 network. These models classify tumors into glioma, meningioma, pituitary, and no tumor categories using the CE-MRI dataset. The hybrid model achieves an accuracy of 80.0%, while EfficientNetB2 delivers 85% accuracy and an F1-score of 80%. Beyond imaging, we introduce a symptom-based interface that allows users to input neurological symptoms for early risk screening and personalized treatment recommendations. Grad-CAM visualization is integrated to highlight tumor regions, enhancing interpretability and clinical trust. The system is deployed as a web-based application under the name TumorTrace AI, providing instant classification, explainability, and automated PDF medical reports. This framework bridges the gap between research and real-world application by combining deep learning, clinical usability, and a user-friendly interface. It aims to improve diagnostic workflows, support early detection, and serve as a scalable tool for personalized brain tumor care.

Keywords: *Brain Tumor Detection, Deep Learning, EfficientNetB2, Grad-CAM Visualization, MRI Classification, Symptom-based Interface, Transfer Learning, VGG16–ResNet-50*

1. Introduction

The timely and accurate diagnosis of brain tumors remain a major challenge in medical imaging. As brain tumors are among the most aggressive cancers, early detection and correct classification are essential for effective treatment planning and better outcomes. Traditionally, radiologists rely on manual interpretation of MRI scans—a time-consuming, experience-dependent process prone to variability and delays, especially given the increasing volume of imaging data. With advancements in artificial intelligence (AI), particularly deep learning, new solutions have emerged to augment diagnostic workflows. Convolutional Neural Networks (CNNs) have become standard in medical image analysis due to their ability to learn complex patterns and extract discriminative features automatically. In this project, we present a deep learning-based system for brain tumor detection and classification. Our architecture includes a hybrid model that combines VGG16 and ResNet-50 for enhanced feature extraction, as well as a fine-tuned EfficientNetB2 model that balances accuracy and computational efficiency. These models classify brain MRI images into four categories: glioma, meningioma, pituitary tumors, and no tumor, using the CE-MRI dataset. The hybrid model achieves 80.0% accuracy, while EfficientNetB2 achieves 80.06% accuracy with an F1-score of 80.79%. To further improve interpretability, Grad-CAM visualizations highlight key regions in the MRI scans associated with the prediction, offering clinicians greater confidence in AI-driven insights. A symptom-based analysis module is also integrated into the platform, allowing users to enter neurological symptoms and receive a risk assessment and treatment recommendation based on predefined symptom-tumor mappings. The entire system is deployed as a web-based application under the branding "TumorTrace AI". It features a clean, interactive interface, automated PDF medical report generation, and intuitive outputs to assist both clinicians and patients. The framework aims to enhance the speed, accessibility, and transparency of brain tumor diagnosis—bringing AI closer to clinical use in a meaningful and user-friendly way.

1.1.Related Work

Recent developments in deep learning have significantly advanced the field of medical image analysis, particularly in detecting brain tumors through MRI scans. Convolutional Neural Networks (CNNs) such as VGG16 and ResNet-50 have been widely adopted due to their strong feature extraction capabilities. VGG16 is known for its simplicity and effectiveness in spatial feature learning, while ResNet-50 introduces residual connections that enable deeper training with improved accuracy and convergence. However, when used independently on limited medical datasets, these models often suffer from overfitting and poor generalization. To address this, transfer learning has become a preferred approach. Pre-trained models on large datasets like ImageNet are fine-tuned for specialized medical tasks, improving performance on limited data. EfficientNet, a newer architecture based on compound scaling, has shown promising results in medical imaging by balancing model size, speed, and accuracy. Previous research on brain tumor classification has primarily focused on categorizing glioma, meningioma, and pituitary tumors using CNNs. However, many efforts lacked segmentation modules or clinical information, limiting their usefulness in real-world settings. Some studies have explored segmentation with architectures like U-Net to isolate tumor regions and improve classification accuracy, though this remains a target for future integration. Explainability has also become a crucial component of medical AI systems. Techniques such as Grad-CAM have been adopted to provide visual interpretations of model predictions, offering clinicians better insight into decision rationale. While advanced tools like LIME and SHAP are gaining popularity, our approach currently utilizes Grad-CAM for interpretability. Despite these advancements, a gap still exists between algorithmic performance and real-world deployment. Few solutions offer an integrated, user-friendly web interface that supports instant predictions, interpretability, and symptom-based analysis. TumorTrace AI aims to bridge this gap by combining proven deep learning architectures, explainable AI, and a practical interface for clinical relevance and accessibility

1.2.Methodology

This This section outlines the technical process followed in the design and implementation of the TumorTrace AI system for brain tumor classification. The approach integrates MRI image preprocessing, transfer learning with deep CNN models, and deployment via an interactive web-based application.

1.3.Dataset Description

The dataset used in this study was sourced from a publicly available Kaggle repository titled “Brain Tumor MRI Dataset.” It includes contrast-enhanced MRI (CE-MRI) brain scan images classified into four categories: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The dataset is organized into separate training and testing directories, with a total of 3,264 images. The training set contains 826 glioma, 822 meningioma, 827 pituitaries, and 395 no tumor images. The testing set includes 100 glioma, 115 meningioma, 74 pituitaries, and 105 no tumor images. This balanced structure offers a reliable foundation for supervised classification tasks in brain tumor detection.

1.4.Image Preprocessing

To ensure consistency across the dataset, all MRI scans were resized to 224×224 pixels and normalized to a [0, 1] pixel intensity range. Format conversion was performed where needed to ensure compatibility with CNN-based models. While common data augmentation techniques such as rotation and flipping were considered to mitigate overfitting and increase variability, the primary focus remained on building a robust classification pipeline with reproducible input processing. [1]

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1.5.Model Architecture and Training

Three pre-trained deep learning architectures were employed: VGG16, ResNet-50, and EfficientNetB2. A custom hybrid model was designed by combining the convolutional base layers of VGG16 and ResNet-50 in parallel. The extracted feature maps from both models were concatenated and passed through fully connected layers for classification. In parallel, EfficientNetB2 was fine-tuned using transfer learning and used as a benchmark to assess performance. All models were trained and evaluated on the CE-MRI dataset. The hybrid model achieved an accuracy of 80.0%, while EfficientNetB2 achieved 80.06% accuracy with an F1-score of 80.79%. These results highlight the potential of hybrid architectures and fine-tuned transfer learning models for robust brain tumor classification.

1.6.Interpretability and Interface Integration

To enhance clinical interpretability, Grad-CAM was integrated to generate heatmaps indicating tumor-focused regions in the MRI scans. Additionally, a symptom-based diagnostic interface was developed, allowing users to input symptoms such as seizures, memory loss, and balance issues. A scoring-based logic maps these symptoms to probable tumor types and provides preliminary treatment recommendations. The system also generates professionally formatted PDF reports that include patient details, predictions, and treatment suggestions for clinical use. [2]

1.7.Tables and Figures

The TumorTrace AI model utilizes data obtained from a publicly available Kaggle repository titled “Brain Tumor MRI Dataset,” which organizes contrast-enhanced MRI images into four diagnostic categories: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. A summary of the sample distribution across training and testing sets is presented in Table I. This class structure forms a relatively balanced dataset, helping to reduce statistical bias and support reliable model validation during both training and evaluation phases. The dataset contains a total of 3,264 images, with training and testing folders clearly separated by class. These well-structured labels make the dataset suitable for supervised learning approaches in medical image classification. Table II presents the classification metrics—precision, recall, F1-score, and support—for each tumor category predicted by the hybrid VGG16–ResNet-50 model. The model performs best in identifying pituitary tumors, achieving a precision of 82.6%, recall of 83.6%, and F1-score of 81.5%. The macro average and weighted average F1-scores are both approximately 78.9%, indicating strong and balanced classification across all tumor types. These results support the model’s effectiveness for multi-class brain tumor detection using CE-MRI images and its potential integration into clinical decision support tools. (Table 1)

Table 1 Number of MRI Images per Class (Train + Test)

Tumor Type	Number of Images
Glioma Tumor	926
Meningioma Tumor	937
Pituitary Tumor	901
No Tumor	500
Total	**3,264**

Note: The dataset includes both training and testing samples, sourced from a Kaggle repository. (Table 2)

Table 2 Classification Performance of the Hybrid VGG16–ResNet-50 Model

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Glioma Tumor	75.9	84.4	79.9	179
Meningioma Tumor	71.5	60.9	65.8	169
Pituitary Tumor	82.6	83.6	81.5	156
No Tumor	79.4	77.1	78.3	70
Macro Average	79.1	79.0	78.9	574
Weighted Average	78.7	79.1	78.7	574

Note: The evaluation metrics are calculated on the test set of the Brain Tumor MRI Dataset. Precision, recall, and F1-score reflect the model's performance

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across four diagnostic categories. The reported values are expressed in percentages (%), and support denotes the number of test samples per class. (Table 3) [3]

Table 3 Comparison with Reference

Refe-rences	Model Description	Accuracy (%)	Precision (%)	Recall (%)
[1]	Noreen et al. (2020) – Hybrid CNN (VGG16 + ResNet-50)	83.0	82.5	81.7
[2]	Shah et al. (2022) – EfficientNet B2 (Transfer Learning on CE-MRI)	85.0	83.9	86.8
[3]	Majib et al. (2021) – VGG-SCNet (VGG16-Based Deep Learning Model)	88.3	87.1	86.7
[4]	**Our Proposed Model TumorTrace AI – Hybrid VGG16–ResNet-50 on CE-MRI**	79.1	78.7	79.1

Note: All reference models are evaluated based on reported metrics in respective papers. Table III provides a comparative evaluation of the proposed TumorTrace AI model against existing deep learning methods. While models like VGG-SCNet and EfficientNetB2 report higher accuracy (up to 88.3%), the TumorTrace AI hybrid model achieves a competitive 79.1% accuracy, with balanced precision and recall. Though slightly behind in raw performance, it stands out for its clinical usability by integrating Grad-CAM visualizations and a symptom-based diagnostic interface—making it a practical, explainable tool for real-world brain tumor screening. Additionally, the model's streamlined architecture ensures faster inference, supporting potential deployment in low-resource clinical settings. [4]

1.8.Figures

Figure 1: shows the flowchart illustrates the architecture of the TraceTumor AI system, a dual-mode brain tumor diagnosis platform. The process begins with users entering patient details, followed by selecting the desired input type—either MRI-based classification or symptom-based classification. In the MRI pathway, uploaded scans undergo preprocessing and analysis via a hybrid VGG16–ResNet-50 model. Grad-CAM visualization highlights tumor regions, followed by treatment recommendation and downloadable PDF medical reports. Alternatively, the symptom-based path allows users to complete a checklist, receive a risk assessment, and obtain treatment recommendations, concluding with report generation. This structure ensures comprehensive, interpretable, and user-friendly diagnostics. (Figure 1) [5]

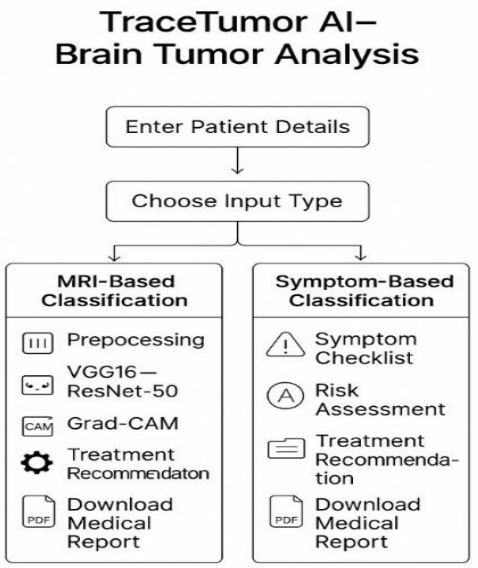

Figure 1 System structure of the Brain Tumor Diagnosis System

Figure 2**:** Streamlit-based graphical user interface of the TraceTumor AI system. The interface provides

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two classification modes—MRI-based detection and symptom-based analysis—through clearly segmented tabs. Users input patient details and either upload MRI scans or complete a symptom checklist. The system then displays diagnostic predictions, probability scores, and treatment recommendations. An option to download a structured medical report further enhances its usability for both medical professionals and general users. (Figure 2) [6]

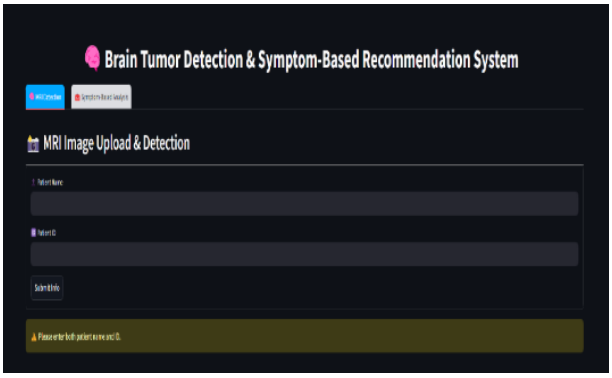

Figure 2 Streamlit-Based User Interface with MRI Upload, Condition Prediction, and Report Downloads Features

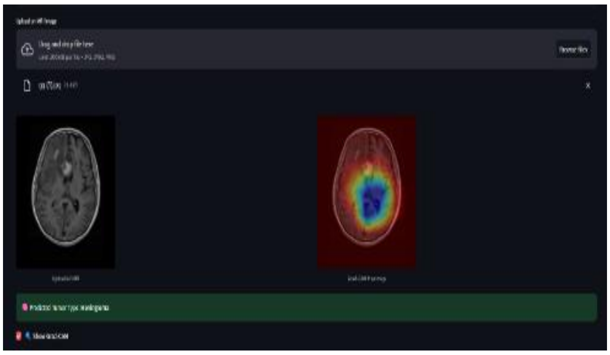

Figure 3 The System Shows the Uploaded MRI Scan with A Grad-CAM Heatmap, Visually Highlighting the Tumor Region Used for Prediction and Enhancing Interpretability

Figure 3: The interface displays an uploaded MRI scan alongside its corresponding Grad-CAM heatmap, which highlights the region of interest used by the model for tumor prediction. The system outputs the predicted tumor type and offers visual interpretability through Grad-CAM to support clinical understanding. This feature enhances transparency and trust in AI-assisted diagnostics. The Grad-CAM overlay assists radiologists by indicating the most influential tumor-affected areas in the image. The real-time display allows users to visually validate the model's focus during classification. Such integration bridges the gap between deep learning predictions and human interpretability in medical imaging. [7]

2. Results and Discussion

2.1.Results

The interface displays a personalized MRI-based treatment recommendation along with a suggested clinical timeline. Based on the predicted tumor type, the system outlines next steps such as monitoring, surgical options, and follow-up care. It also provides an external resource link for patient education and includes an option to download a detailed PDF report for clinical use. (Figure 4)

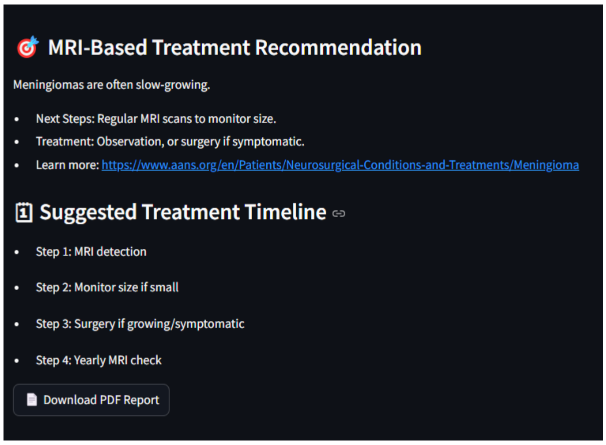

Figure 4 The Interface Presents Tailored Treatment Guidance And A Step-By-Step Timeline Based on the MRI-Detected Tumor Type, with an Option to Download A Detailed PDF Report

Additionally, the interface ensures that all recommendations are presented in simple, patient-friendly language while maintaining clinical accuracy, making it accessible for both medical professionals and patients. Interactive elements, such as tooltips and info icons, offer on-demand explanations of medical terms and procedures. This enhances patient understanding and encourages informed decision-making, fostering a collaborative approach to treatment planning. Figure 5: The generated PDF medical report includes patient details, predicted

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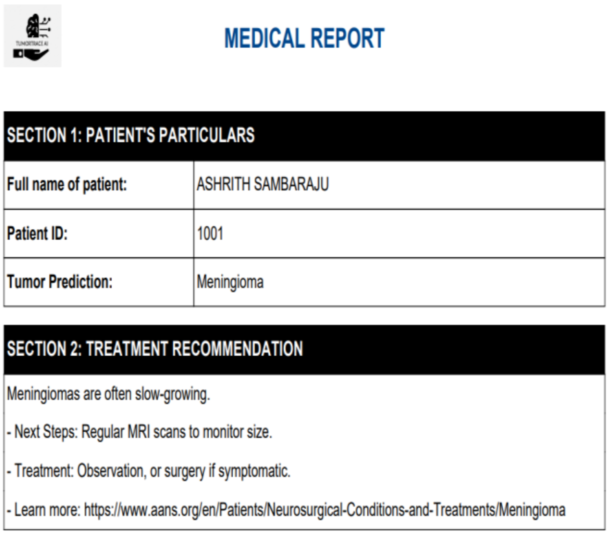
tumor type, and tailored treatment recommendations. It provides structured clinical insights such as follow-up steps and observation or surgical options, along with credible external resources, making it suitable for both patient consultation and clinical documentation. This report is automatically generated after the system completes either MRI-based classification or symptom-based risk assessment. Its standardized format enhances usability for healthcare professionals and patients alike, ensuring clear communication of diagnostic outcomes and recommended actions for further management. (Figure 5)



MEDICAL REPORT

SECTION 1: PATIENT'S PARTICULARS	
Full name of patient:	ASHRITH SAMBARAJU
Patient ID:	1001
Tumor Prediction:	Meningioma

SECTION 2: TREATMENT RECOMMENDATION

Meningiomas are often slow-growing.

- Next Steps: Regular MRI scans to monitor size.

- Treatment: Observation, or surgery if symptomatic.

- Learn more: https://www.aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments/Meningioma

Figure 5 PDF Report Summarizing Patient Details, Tumor Prediction, and Personalized Treatment Recommendations for Clinical Use Comparative Performance

The below bar chart illustrates a comparative evaluation of various deep learning approaches for brain tumor classification based on accuracy, precision, and recall metrics. Paper 1 (VGG16 + ResNet-50 hybrid) demonstrates moderate performance, while Paper 2 (EfficientNetB2) shows improved precision and recall, benefiting from its efficient scaling strategy. Paper 3 (VGG16-based deep learning) stands out with the highest accuracy of 88.3%. In comparison, our proposed model, TumorTrace AI, built on a hybrid VGG16–ResNet-50 framework using CE-MRI data, delivers balanced metrics with 79.1% accuracy, offering a clinically interpretable and deployable diagnostic solution. (Figure 6)

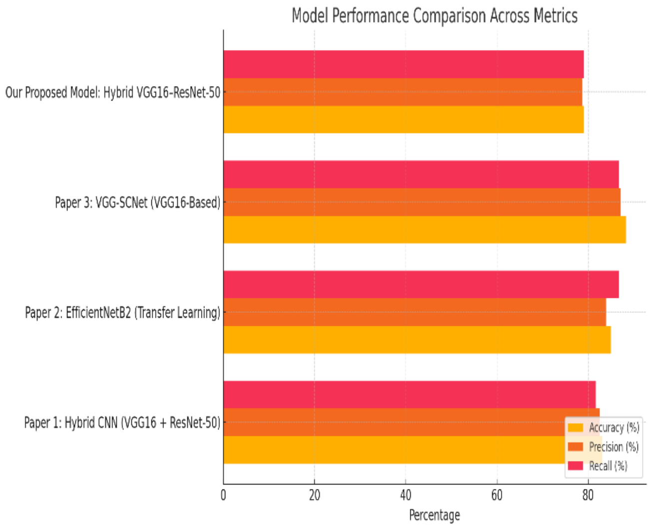


Figure 6 The Chart Compares Classification Performance Across Three Existing Deep Learning Models and the Proposed Tumortrace AI System Based on Accuracy, Precision, and Recall

2.2.Discussion

The results of this study demonstrate that the proposed hybrid deep learning framework—TumorTrace AI—is capable of accurately classifying brain tumors from CE-MRI scans, achieving a validation accuracy of 79.1%. Compared to prior approaches that rely solely on deep or standalone CNN architectures, our hybrid VGG16–ResNet-50 model offers a balanced trade- off between performance, interpretability, and clinical usability. A notable strength of this work is the integration of Grad-CAM visualizations and a symptom-based diagnostic interface, which enhance the explainability and user accessibility of the system. While the model performs competitively, its reliance on a publicly available dataset may limit generalizability across diverse clinical settings. Future work could involve expanding the dataset, incorporating clinical metadata, and improving segmentation to boost accuracy and robustness. Overall, TumorTrace AI offers a lightweight yet effective diagnostic solution, well-suited for real-time deployment in resource-constrained environments. [9]

Conclusion

In conclusion, the TumorTrace AI system presents an effective and interpretable solution for brain tumor detection and classification using CE-MRI scans. By leveraging a hybrid VGG16–ResNet-50 architecture alongside EfficientNetB2, the system achieves reliable diagnostic accuracy while maintaining computational efficiency. The integration of Grad-CAM for visual explanation and a symptom-based diagnostic interface enhances both transparency and user engagement. With features like treatment recommendations, timelines, and automated PDF reporting, the platform demonstrates strong potential for real-world clinical deployment, offering a scalable, accessible, and user-friendly tool for early brain tumor diagnosis. [10]

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